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Level Sets Method and Corner Detector Fused Approach to Image Classification

Xin Wang[+]

School of Railway Power and Electrical Engineering, Nanjing Railway Institute of Technology, Nanjing, China

Abstract. This paper presents a framework for detecting objects in images. The motive of this research can be found in onsite requirements. We focus on the practical needs on distinguishing salt called purity from impurities, which are sand, soil, and other substance in the heaped salt on a conveyer belt. Our corner detector is given by an auto-correlation function about images. In this work, basing on image energy, we formulate the auto-correlation function on image energy to construct a piloting set which includes possible elements to classify objects and the impurity object in order to navigate the front propagation of the level sets. We finally use level set method to detect the topologic changes of curves and to catch the objects/impurity. The available has been proved by applying this approach into an industrial image shown in this paper.

Keywords: Image, Corner Detector, Auto-correlation , Image, Level Sets Method

1. Introduction

Image vision technology has matured substantially in the last decade to be successfully applied to a variety of industrial tasks. Three methods, optical device-based, algorithm-based technology and special image deice-based are the main in industrial applications. In the field of factory automation, successful applications of image technology are roughly divided into assembling and inspection. For example to decide a 2D positions as analogical robot sensor or 3D positions when measuring automobile's body, surface inspections, inspecting LSI pattern, and mask and printing board etc [1][2][3][4].

With the development of cheaper color cameras, more people have been more and more interested in digital image application or algorithm technologies. There are many successful industrial applications in the past years [5][6][9], but the past works mostly depend on the constraints of possible pattern matching. Image technologies for applications, especially in industry, are strong case-dependence. Because we want to solve our problem by image technology instead of paying more cost to some special material inspection sensor device, it is our intelligent selection to develop the image algorithm.

Our corner detector is given by an auto-correlation function about images. The aim of this paper is to introduce level set methods based on the auto-correlation techniques and provide a basic framework for industrial applications.

The key idea of Level set methods in image plane is implicit curve evolution in the planer image. We notice the fact that when purity and impurity are mixed in an image, their different textures and gray values are certainly bringing about gradients changes. These changes show us a lot of clues for image classification and recognition. We induce the propagating interfaces by those high image energy parts to label the object from their background. The evolving surface of impurity is presented as the zero level function [13][14][15]. To reduce the computation cost required by level set formulation scheme, a new approach exploited by image

[+] Corresponding author.
E-mail address: bodabo2002@sohu.com.

auto-correlation is proposed. Making a piloting set is a process calculating image energy. It supports level set function a limited domain and speed up evolving front effectively.

The present approach is described as followings. The image pre-process is at the first. This will take us the advantages that the changes we are interested in will not be suppressed by some smoothing, which tends to suppress the effects of noise. We introduce the important auto-correlation method to pilot the interest point in an image. Such a fact has been noticed that the border between and soil certainly cause an obviously image energy changes i.e. gray value changes. We will illustrate either how the auto-correlation algorithm catches these changes or how its results give us a coarse pilot on the objectives we are interested in. We want to classify the coarse positions by some local windows, to inspect the detail changes and compare the results with our preset models, which are the features of their Gaussian distributions. Based on the similarities between the results and the models, we judge whether a class is accepted as an object soil or not [7] and these are our following works.

In this paper, we give the auto-correlation model in next section. The pre-process and classification are also introduced in the section 2. Section 3 describes the principle of curve evolution based on level set methods. Some experimental results and discussions are at the last.

2. Corner Detecter based Algorithm

Our source images should be color. A color image consist red, green, blue three base colors which gray vales are kept by eight digital bits respectively. Fig.1 gives two dark dots which are soil blocks in white salt. It shows typical sizes of mixed substance in images.

The present approach deals with the problem as followings. An image is pre-processed at the first. This will take us the advantages that the changes we are interested in will not be decreased and the effects of noise are suppressed. We introduce the important auto-correlation method to pilot the interest point in an image. Such a fact has been noticed that the border between and soil certainly cause an obviously image energy changes i.e. gray value changes. Section 4 will illustrate either how the auto-correlation algorithm catches these changes or how its results give us a coarse pilot on the objectives we are interested in. We continuously classify the coarse positions by some local windows, to inspect the detail changes and compare the results with our presenting models, which are the features of their Gaussian distributions. Based on the similarities between the results and the models, it is judged whether a class is accepted as a mixed substance or not.

2.1 Image pre-precess

In general, any change of significance to us has effects over a pool of pixels. For many kinds of noise model, large image derivatives due to noise are an essentially local event. This means that smoothing a differentiated image tends to support the changes we are interested in and to suppress the effects of noise [8]. In a pre-process, the smoothing filter can be chosen by taking a model of an edge and using some set of criteria to choose a filter that gives the best response to that model. It is difficult to pose this problem as a two-dimensional problem because edges in 2D can be curved. Conventionally, the smoothing filter is chosen by formulating a one-dimensional problem and then using a rotationally symmetric version of the filter in 2D. In our case, we select a nonlinear rank-value median filter for image pre-process. We take all the gray values of the pixels which lie within the filter mask and sort them by ascending gray value. The rank-value filter only differs by the position in the list from which the gray value is picked out and written back to the center pixel, and it is well known as median filter. Let $M_1=M_1(n, n)$ (n is odd) be those gray values around a pixel. To an array $M_2=M_2(\mathrm{k})$ ($k=1, 2, S=n\times n$), this filter use the value $M_2(S/2)$ as it responses. This made us easily adjust the smoothing scales to different size of objects.

2.2 Corner detector: auto-correlation on image energy

Corner detection is important in computer vision and object recognition systems. Corners where image energy changes occur on the direction of shape boundary provide significant clues in the description of object shape. In the approach, the corner detector is given by a mathematical auto-correlation model [7][10]. Let $I(X)$ (also denoted as I) be the image function in an image frame. Given a shift $(\Delta x, \Delta y)$ and $X=(x, y)$, $X\in R^2$. The auto-correlation function is defined as:

$$f(x,y)=\sum_{w}(I(x_k,y_k)-I(x_k+\triangle_x,y_k+\triangle_y))^2 \tag{1}$$

where (x_k, y_k) are the points in the working local widow *w*. Based on the Taylor expansion:

Figure 1. The soil grains image.

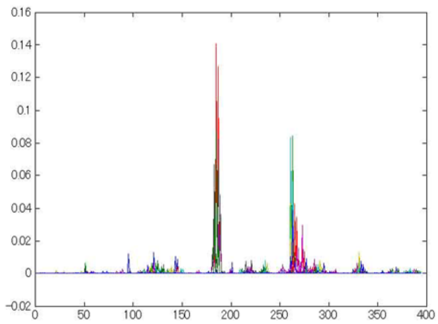

Figure 2. The horizontal is the horizontal coordinate in Fig.1; the vertical is the vaules of cost function M(X) in Eq. (6).

$$\begin{aligned} &I(x_k+\triangle_x,y_k+\triangle_y)\\ &=I(x_k,y_k)+I_x(x_k,y_k)\Delta x+I_y(x_k,y_k)\Delta y+,...\\ &\approx I(x_k,y_k)+(I_x(x_k,y_k)\ I_y(x_k,y_k))\begin{pmatrix}\Delta x\\ \Delta y\end{pmatrix}\end{aligned} \tag{2}$$

where $I_x=\partial I(X)/\partial x$, $I_y=\partial I(X)/\partial y$. Substituting the above approximation (5) into (4), we obtain:

$$\begin{aligned} f(x,y)&=\sum_{w}\left(I_x(x_k,y_k)\ I_y(x_k,y_k)\begin{pmatrix}\Delta x\\ \Delta y\end{pmatrix}\right)^2\\ &=\sum_{w}(\Delta x\ \Delta y)\begin{pmatrix}I_x^2 & I_xI_y\\ I_xI_y & I_y^2\end{pmatrix}\begin{pmatrix}\Delta x\\ \Delta y\end{pmatrix}\end{aligned} \tag{3}$$

$$\begin{aligned} f(x,y)&=(\Delta x\ \Delta y)\left[\sum_{w}\begin{pmatrix}I_x^2 & I_xI_y\\ I_xI_y & I_y^2\end{pmatrix}\right]\begin{pmatrix}\Delta x\\ \Delta y\end{pmatrix}\\ &=(\Delta x\ \Delta y)[J(x,y)]\begin{pmatrix}\Delta x\\ \Delta y\end{pmatrix}\end{aligned} \tag{4}$$

To $I_p(X)=G_p*I$, $*$ is the convolution operation, we change $J(x, y)$ as $\nabla I(\nabla I)^T$, build up a transform relation $H(X)$ in a local window about X.

$$= \sum_{w} (\Delta x \; \Delta y) \begin{pmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix}$$

$$\mathrm{H}(X) = T(X) * \sum \left\{ \nabla^I (\nabla^I)^T \right\} \quad (5)$$

$$= T(X) * \sum \begin{Bmatrix} (G_x * I)^2 & (G_x * I)(G_y * I) \\ (G_x * I)(G_y * I) & (G_y * I)^2 \end{Bmatrix}$$

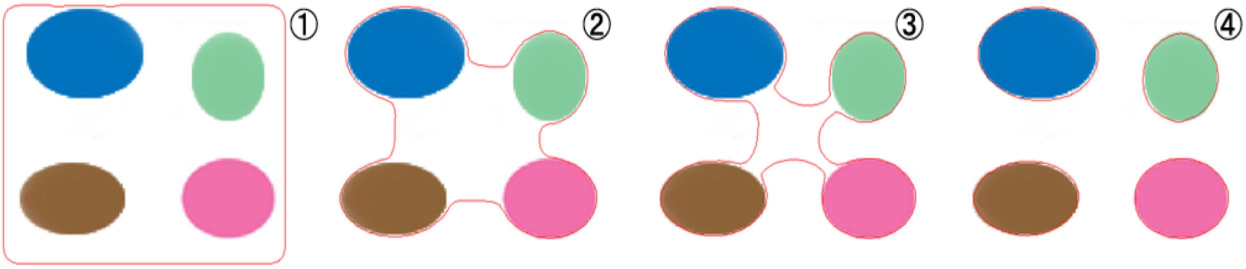

Figure 3. 1: the initial curve and objects; 2 and 3: the curve is propagating with time; 4: All the four objects are caught. The objects are surounded by four curves seperated from the initial curve in 1 perfectly.

where G is a Gaussian with standard deviation one, $G_x = \partial G / \partial x$, $G_x = \partial G / \partial y$. $T(X)$ is a weight mask to weight the derivatives over the window. In (8), there relations $\partial I/\partial x = \partial/\partial x * I$, $\partial/\partial x*(G*I) = (\partial/\partial x*G)*I = \partial G/\partial x*I$. This matrix captures the local structure. The eigenvectors of this matrix are the principal curvatures of the auto-correlation function. We consider a cost function $M(X)$:

$$M(X) = E[H(X)] + K[H(X)] \quad (6)$$

2.3 Image classification

$M(X)$ in (6) gives the distributions of image energy clearly. We classify those points piloted by $M(X)$ further. Assume the i_{th} point $P_i(X)$ be presented by a complex OP_i, the j_{th} point $P_j(X)$ by OP_j, to a constant d_1, if it is true that

$$\left| OP_i - OP_j < d_1 \right| \quad (7)$$

$P_i(X)$ and $P_j(X)$ are put into same set C^k, $C^k \cap C = C^k$. C is defined as the classification set.

$$C = \bigcup_{k}^{S} C^k \quad (8)$$

where s is a preset constant to decide the subsets in C. The elements in C^k are coarse results classified. Assume the center of gravity of the elements in C^k be $P_c(X)$, $M(X)$ will be recalculated by (5) and (6) with a smaller preset constant d_t ($d_t < d_{t-1}$, $t \le constant$) around $P_c(X)$ in a smaller local window several times. If the results under d_t will be treated as the part of the soil, it becomes the results recognized. The reason we did this is that it is impossible to get complete pixels about the object or soil, for the reasons that the surface of the soil reflect light in all direction etc., smaller d_t can use more fine resolutions to analyze objectives.

3. Skeleton of Level Sets Method

Level sets method add dynamics to implicit surfaces. The key idea that started the level set fanfare was the Hamilton-Jacobi approach to numerical solutions of a time-dependent equation for a moving implicit surface.

Given a moving closed hypersurface G(t), we wish to produce an Eulerian formulation for the motion of the hypersurface propagating along its normal direction with speed F, where F can be a function of various arguments, including the curvature, normal direction, etc. This propagating interface is embed as the zero level set of a higher dimensional function $\phi(\mathbf{x}, t)$ (also denoted as ϕ in this paper). Let $\phi(\mathbf{x}, t{=}0)$, where $\mathbf{x}$ is a n-dimension space, be defined by

$$\phi(x, t = 0) = D \quad (9)$$

where D is the signed distance from $\mathbf{x}$ to G(t=0), and plus/minus sign is chosen if the point $\mathbf{x}$ is outside/inside the initial hypersurface G(t=0). Thus, we have an initial function ϕ ($\mathbf{x}$, t=0) with the property that

$$G(t=0) = (x|\phi(x,t=0)=0) \tag{10}$$

The goal is to produce an equation for the evolving function ϕ ($\mathbf{x}$, t) which contains the embedded motion of G as the level set ϕ=0. Let $\mathbf{x}$ be the path of a point on the propagating front. That is, $\mathbf{x}$ (t=0) is a point on the initial front G(t=0), and d$\mathbf{x}$/dt=F($\mathbf{x}$) with the vector d$\mathbf{x}$/dt normal to the front at $\mathbf{x}$. Since the evolving function ϕ ($\mathbf{x}$, t) is always zero on the propagating hypersurface, we must have the constraint

$$\phi(x,t) = 0 \tag{11}$$

By the chain rule,

$$\phi_t + \nabla(x,t)x_t = 0 \tag{12}$$

we then have the evolution equation for ϕ ($\mathbf{x}$, t)

$$\phi_t + F|\nabla\phi| = 0 \tag{13}$$

with a given value of ϕ ($\mathbf{x}$, t=0). This is referred as Hamilton Jacobi type equation because, for certain forms of the speed function F, we obtain standard Hamilton Jacobi equation. Because ϕ ($\mathbf{x}$, t) remains a function as it evolves, we may use a discrete grid in the domain of $\mathbf{x}$ and substitute finite difference approximations for the spatial and temporal derivatives. We use a uniform mesh of spacing h, with grid nodes ij, and employing the standard notation that ϕ_{ij}^n is the approximation to the solution ϕ ($ih, jh, n\,\delta t$), where δt is the time step, we may write

$$\frac{\phi_{ij}^{n+1} - \phi_{ij}^n}{\delta t} + (F)(\nabla_{ij}\phi_{ij}^n) = 0 \tag{14}$$

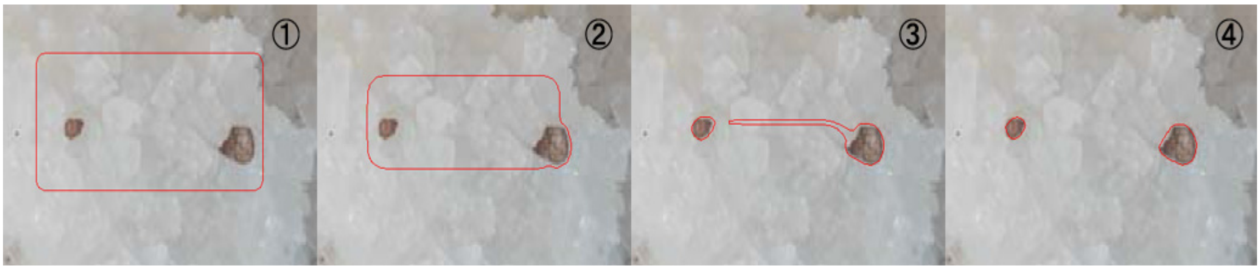

Figure 4. The approach in application. 1: starting from a contour based on the corner detector; 2 and 3: the curve in a front propagation; 4: the objects are caught.

Here, we have used forward differences in time, and let ϕ_{ij}^n be some appropriate finite differences in time, and let $\nabla_{ij}\phi_{ij}^n$ be some appropriate finite difference operator for the spatial derivative. To a given speed function F, we update the front by the modified version of an Engquist-Osher scheme [13]. Fig. 3 illustrates the front propagation on our designed model from left to right.

4. Experimental Results and Discussions

We compute a practical image, which was taken on-site, by the proposed algorithm. In Fig. 4, using the original images on the left, we indicated the processes. Based on the result of Eq.(5) and Eq.(6), the positions of image energy are detected. We have gotten two positions or two significant $M(X)$. After locating the two positions, we gave the closed initial front curve for evolution. This decrease the computation cost obviously. The results in Fig. 4 also show us that $M(X)$ bring us less image noise in the closed front curve and, this is very helpful for the recognition using the finished evolution results. Fig. 4-4 show that the contours of the objects are caught perfectly. This is one of successful applications by means of the advantage of the level sets active contour technique based on corner detector.

5. Conclusions

We proposed in this work a piloted level set methods. This approach uses traditional rank-value median filter as pre-processor, creates an image energy model to lead an initial front propagation in order to perform classification and calculate features about their textures and so on for the purpose of recognition.

When different kinds of objects/grains appear on the same image, most of them will bring about image energy changes presented by the form of gray gradients. The auto-correlation function is excellent way to describe these features, especially in the case of objectives have the global dominant positions in an image, just like the case of the soil mixed in salt. The finished front propagation can give more information for recognition. We can adjust the threshold of the cost function from coarse to fine in a widow around piloted positions dynamically. Then those features can be compared with their models made in advance. Not limited by this application, the developed technique will be also available when the environment is changed, with some modification. Though this approach faces the problem of computation cost, it still is a basic frame work.

In this algorithm, if the objects don't have obvious energy features in a global detection, it will cause s in Eq.(8) increased, and hard to be classified. We suggest s should be maximum three, number constrain companies it, or it is an intelligent way to consider this problem from other bases.

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